

Index Option Greek Analysis with Heikin-Ashi Transformed Data and Its prediction with Artificial Neural Network

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ABSTRACT

This paper analyses the Index Option Greek with respect to a transformed data set of Index that has been Heikin Ashi Transformed. It has been noted that Heikin Ashi Transformation can provide better prediction than normal data and the noise effect can also be used to filter out if volume weights are also considered. This paper tries to predict option greeks for index option with the help of a Neural Network setup. Since option greeks play a very important role in understanding the correct pricing of index option, the paper provides some useful insights in such models.

Keywords: Heikin Ashi Transformation, index option, option Greek, Neural Network, Stock Market Analysis, Time series filtering.

I. INTRODUCTION

Options are a very flexible instrument used in stock market to migrate risk or to hedge existing positions. Index option allows investor to reduce risk associated with global events like macro policy changes or political changes without squaring off existing portfolio. However, these types of instruments are very complex and their value is not only is affected by the uncertainty of the underlying but also the demand supply of options itself.

Options are contracts that have a set time period. While stocks can be held for as long as investor wishes, option on the other hand has a limited life. After the time has expired, the contract will yield some value ranging from zero to potentially unlimited. There are two types of options that exists in such instruments are “call options” and “put options”. While call options allows the owner to buy certain stock at a fixed price (irrespective of actual stock position). The put option allows owner to sell a stock at a certain price (irrespective to its actual position). As human beings. we are already curious of uncertain events and their prediction. Neural network framework has become the science of examining uncertain information and understanding its behaviour. The process of understating the hidden dynamics of data can

provide incredible insights. High power machine can churn out data into profitable patterns far easily now.

Neural network is system that behave like human brain and allow machine to find hidden patterns just like human beings. If a large enough dataset is available then neural network can learn its properties and make educated guesses based on the learning (Guresen et al., 2011) . One of the most desired fields of such research includes stock market.

Stock market is a very complex system. It behaves like a type 2 chaotic system where every information changes its behaviour. place with tons of information. Stock market data generates patterns, that when analysed can provide better opportunities for decision-making. But stock market data is full of noise. Such noise can be a short-term fluctuation in stock market data or may be long term trend shift.

We have already demonstrated that such noise can interfere with learning of neural network and hence reduces the effectiveness of learning and its effectiveness (Sharma and Chauhan, 2019). The Heikin-Ashi transformation has worked remarkably well reducing noise and its effect can be further improved using Vix Index data.

Researchers (Adam et al., 2016) (Torkkeli and Tuominen, 2002) have demonstrated the importance of prediction system as a favorable system for finance managers and incorporating many systems for fund management. Such connection of selection of technology and company is vital (Boyacioglu and Avci, 2010) for a sophisticated driven system. Artificial Neural network has been a very important learning system (Adam et al., 2016) and it has provided a definite edge for its user. The effect of neural network and genetic algorithm has been researched (El-Shorbagy et al., 2016) and found to be very crucial for modeling. Neural network for trend determination (Xiong et al., 2015) and optimized neural network (Boyacioglu and Avci, 2010) are a few key methods to work with. Many researchers have incorporated hybrid models (Sun et al., 2016) and had early success. Generating buy and sell signal using deep neural network (Yeh et al., 2011) as well as a self-organizing rule based system (Xiong et al., 2015) perform very well. Effect and result of ANN on NASDAQ and QQQ (Qiu et al., 2016) and results are in line with expectations.

Now Options are very different instrument used for hedging purposes. However the most remarkable work that was produced in estimation of the value of a index option was given by Fischer Black, and Myron Scholes (Black and Scholes, 1973). The black Scholes differential equation gives us a fair value of a given call or put option with respect to underlying and the length of the contract. This differential equation is used as a benchmark to measure the neural network's performance.

II. METHODOLOGY

Here we introduce the basic concept of Heikin Ashi transformation. The transformation is applied at the OPEN, HIGH, LOW, CLOSE of index and a new set of OPEN, HIGH, LOW, CLOSE is obtained. This will act as new set of input for next output.

Transformation rules:

Let $O_{current}$, $H_{current}$, $L_{current}$, $C_{current}$ represents current open, high, low, close values.

Let O_{Prev} , H_{Prev} , L_{Prev} , C_{Prev} represents Previous day/period open, high, low, close values.

Then Heikin-Ashi values (HA) are calculated as:-

$$HA_{Close} = (O_{current} + H_{current} + L_{current} + C_{current}) / 4$$

$$HA_{Open} = (HA_{OpenPrev} + HA_{ClosePrev}) / 2$$

$$HA_{High} = \text{Maximum of the } H_{current}, HA_{Open} \text{ or } HA_{Close}$$

$$HA_{Low} = \text{Minimum of the } L_{current}, HA_{Open} \text{ or } HA_{Close}$$

Now for the Option pricing we use Black Scholes equation to calculate its fair value and then compare it with value predicted by the Neural network.

The Black Scholes Differential equation for European style option is

$$\frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} + rS \frac{\partial V}{\partial S} - rV = 0$$

The fair value of call option is given by

$$C_E(S, t) = N(d_1)S - N(d_2)X e^{-rT}$$

And value of put option is given by

$$P_E(S, t) = N(-d_2)X e^{-r(T-t)} - SN(-d_1)$$

Where

$$d_1 = \frac{\ln\left(\frac{S}{X}\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}}$$

$$d_2 = \frac{\ln\left(\frac{S}{X}\right) + \left(r - \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}}$$

For both, as above:

- N is the cumulative distribution function of the standard normal distribution
- T is the time to maturity (expressed in years)
- S,t is the spot price of the underlying asset
- K is the strike price
- r is the risk free rate (annual rate, expressed in terms of continuous compounding)
- σ is the volatility of returns of the underlying asset

Every Option has following greeks that provide another point of interest to measure their values. These are called as option greeks and are defined as follows:

Delta provides the variation of V with respect to S

$$\text{Call delta} = e^{-qt} * N(d_1)$$

$$Put\ delta = e^{-qt} * (N(d_1) - 1)$$

Gamma is the 2nd Derivative of V w.r.t. S given by

$$Gamma = \frac{e^{-qt}}{S_0 \sigma \sqrt{t}} * \frac{1}{\sqrt{2\pi}} * e^{-\frac{d_1^2}{2}}$$

Vega is the Derivative of V w.r.t. Volatility

$$Vega = \frac{1}{100} S_0 e^{-qt} \sqrt{t} * \frac{1}{\sqrt{2\pi}} * e^{-\frac{d_1^2}{2}}$$

Theta provides the time decay factor of option given by

Call theta =

$$= \frac{1}{T} \left(- \left(\frac{S_0 \sigma e^{-qt}}{2\sqrt{t}} * \frac{1}{\sqrt{2\pi}} * e^{-\frac{d_1^2}{2}} \right) - r X e^{-rt} N(d_2) + q S_0 e^{-qt} N(d_1) \right)$$

Put theta =

$$= \frac{1}{T} \left(- \left(\frac{S_0 \sigma e^{-qt}}{2\sqrt{t}} * \frac{1}{\sqrt{2\pi}} * e^{-\frac{d_1^2}{2}} \right) + r X e^{-rt} N(-d_2) - q S_0 e^{-qt} N(-d_1) \right)$$

We use the Heikin-ashi Transformed data with a {4,9,1} 3 Layer Neural Network. The training data is used to find the value of both option greeks and then normalized for positive values and compared with that produced by Black Scholes Model.

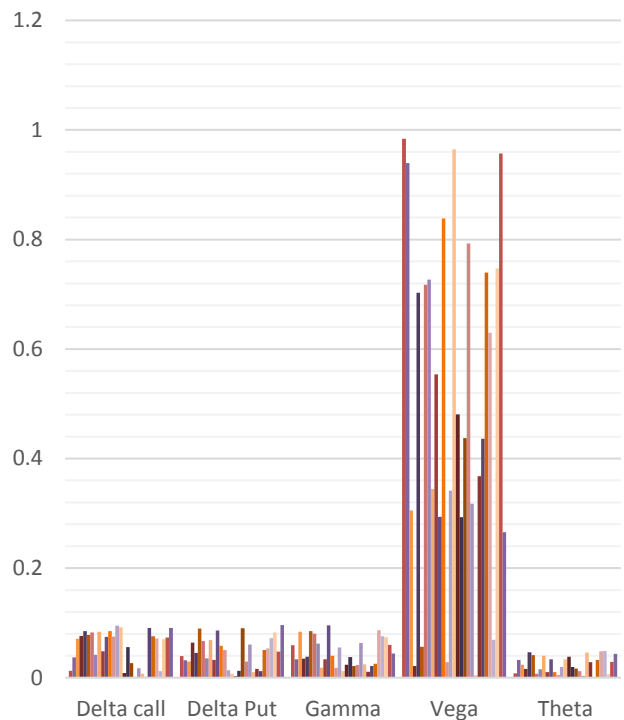
III. RESULTS AND DISCUSSION

A. Standard Error in Prediction for Option Greeks

Our testing results have found a huge error rate for volatility (Vega) computation. Which signifies either the current setup is not suitable for volatility calculations or volatility may not be a variable in prediction. The variation in volatility prediction is very large making it nearly useless for prediction. However, the other greeks are well in an acceptable range. All values have been converted into percentage for better comparison.

	Delta call	Delta Put	Gamma	Vega	Theta
Std Dev	3%	3%	3%	31%	2%
Average	6%	5%	5%	50%	2%

Option Greek Prediction Error



IV. CONCLUSION

It is clear that Vega Greek is way off for being useful in any model as the error rate shoot more than 100% sometimes, which basically means that Vega is out of NN's prediction range. However other greeks are well in range for a good enough model. Variation in Vega prediction cannot be explained at this point, which may indicate that a further study might be needed. A fine tuning in network layer or number of neurons may be considered in further studies.

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